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To cite this article: Vasily Zyuzin *et al* 2021 *J. Phys.: Conf. Ser.* **1727** 012014

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Computer vision system for the automatic asbestos content control in stones

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Abstract. The paper discusses the results of the first stage of research and development an innovative computer vision system for the automatic asbestos content control in stones veins at an asbestos processing factory. The discussed system is based on the applying of a semantic segmentation artificial neural networks, in particular U-Net based network architectures for solving both: the boundaries of stones segmentation and veins inside them. At the current stage, the following tasks were solved. 1. The discussed system prototype is developed. The system is allowing to takes images of the asbestos stones on the conveyor belt in the near-infrared range (NIR), avoiding the outer lighting influence, and processing the obtaining images. 2. The training, validation and test datasets were collected. 3. Substantiated the choice of the U-Net based neural network. 4. Proposed to estimate the resulted specific asbestos concentration as the average relation of all the veins square to all stones square on the image. 5. The resulted deviation between obtained and laboratory given results of the asbestos concentration is about 0.058 in the slope of graduation curve. The farther improvement recommendations for the developed system are given.

1. 1 Introduction

Analysis and control of composition of processed products at mining processing factories, in particular asbestos processing factories, is one of the priority tasks in the mining industry [1–4]. Frequently such control is provided either visually (as instant control performed by mining specialists) or in the laboratory (for estimating average product quality ratings by shift) [1]. The carried-out survey of mining specialists (on the asbestos processing factory in the Sverdlovsk Oblast, Russia) shows, that however, the laboratory tests are providing better accuracy, but has a high cost and requires too much time (about 8 hours on the surveyed factory). At the same time, information about the current product quality is necessary for effective management of the factory productivity.

The visual product content control carried out by a geologist has several drawbacks, in particular, it leads to the mistakes connected with subjective perception, and in essence and, it is more an art, than a scientific approach, which also requires a long training of a staff of specialists. In particular, often the mining specialists cannot formally describe how they carried out control. However, as shown in the literature, this kind of control can be automated, for instants, in such tasks as coal sorting [1]; estimation ore size distribution [2]; coal and rocks determination on the image [3] and classification their types [4]; the allocation of inclusions in ore [5] and many other.



Nowadays, artificial neural network-based semantic segmentation methods most popular to visual control automatization. The main advantage of this approach is automated feature selection during network training regardless of the complexity of their formal description. However, the training routine requires dataset large enough for all feature correct determination [6].

One of the most popular classes of semantic segmentation neural networks up-to days is based on the U-Net architecture [7]. U-Net neural networks were originally proposed for the analysis of medical images, where it showed high accuracy, in particular for small size objects [8, 9]. However, nowadays, this kind of networks obtaining popularity in many other applications, in particular in the mining industry [1–5]. For instance, in paper [1], U-Net was applied for automatization of sorting gangue from raw coal with training only on 60 images (54 for training and 6 for the test). In paper [2] U-Net was applied for automatization of ore size distribution estimation by conveyor belt operation images. At the same U-Net-based architectures can be applied even to analyses small size features with rare allocation on images, for instance, paper [10] apply U-Net to segmentation of plants roots in the soil.

The aim of this paper is an innovative computer vision system development for the automatic asbestos content control in stones veins at an asbestos processing factory using U-Net based semantic segmentation neural networks.

2. Dataset description

The scheme and photo assembled prototype of the developed computer vision system for the dataset collection are shown in Figure 1. The snapshots were carried out using a Dalsa Genie Nano M2590NIR computer vision camera with a 1-inch matrix and increased sensitivity in the NIR range, with resolution 2590×2048 pixels [11]. The snapshots were taken with using near infra-red filter with a cut-off frequency 850 nm. The filter allows one to avoid outer lighting influence on the obtained images. In addition, it is known that the maximum of the asbestos thermal radiation lay in the NIR range [12]. The camera was placed at a distance of 900 mm from the conveyor belt, which was 400 mm wide. This ensured that the entire width of the conveyor belt was captured in the obtained images. For providing asbestos NIR radiation in the images the halogen lamps were applied, because for these lamps the radiation maximum laying in the IR range.

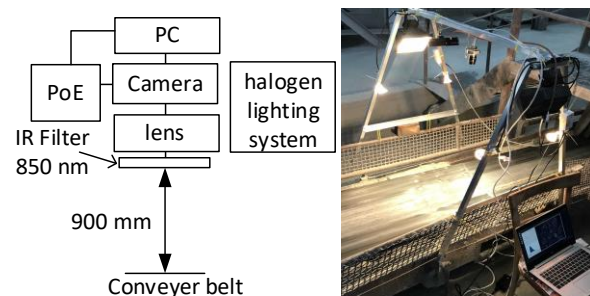


Figure 1. Photo of the developed system (left) and image obtaining and processing scheme (right).

The two datasets of asbestos ore images were collected using the described above system.

– The dataset № 1 was collected from 46 images of lonely stones in laboratory conditions. The typical image and labelled mask of stone boundaries and veins are shown in Figures 2 A – C correspondingly.

– The dataset №2 was collected from 134 images of stones on the fixed conveyor belt of asbestos processing factory. For the dataset collection, 50 samples of 10-20 stones each were randomly selected and snapshotted in different positions obtained by its random mixing and turning. For each of samples were estimated the asbestos content by the laboratory tests. The typical image and labelled mask of stone boundaries and veins are shown in Figures 2 D – F correspondingly.

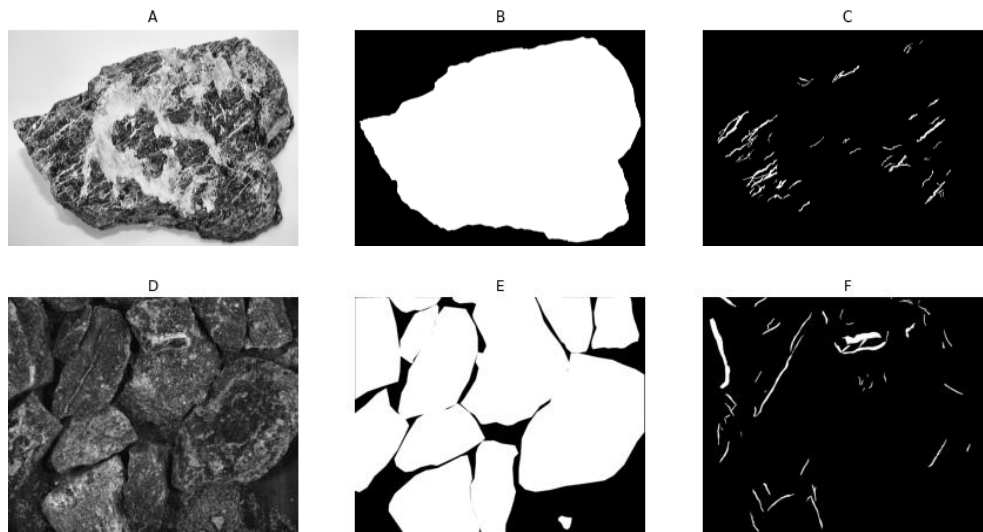


Figure 2. The typical image and labelled mask of stone boundaries and veins for the dataset № 1 (A – C correspondingly) and for the dataset № 2 (D – F correspondingly).

3. CNN architecture

The U-Net based semantic segmentation artificial neural network architecture was applied for both: the boundaries of stones segmentation and veins inside them. The U-Net block-scheme is shown in Figure 3.

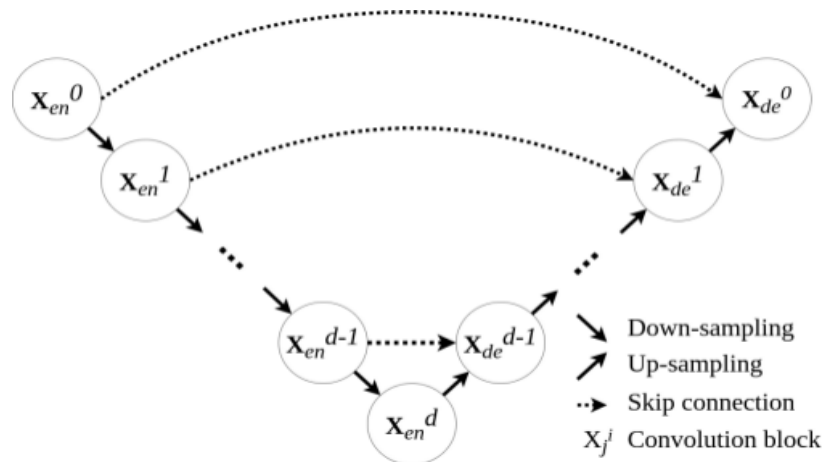


Figure 3. U-net architecture (X_{en} – encoder block, X_{de} – decoder block).

Let us recall that the standard U-Net scheme consists in the encoder part (convolution part) and decoder part (deconvolution part). At the same time, each block of the encoder and decoder of the U-Net network is realized from the so-called pairwise convolutional layers with joint activation [7]. This provides, in contrast with feedforward-based architectures, features transfer from encoder block to the corresponding decoder block. This leads to avoiding loss of small reconstructed (segmented) objects details in the decoder part.

In the carried-out investigation, standard encoder block was replaced with the EfficientNet-B3 block, taken from the paper [13]. Note that, the initial weights of EfficientNet-B3 block was taken as weights obtained by its pre-training on the ImageNet dataset [14]. In the training, the Dice coefficient [6] was applied as a quality metric. The Adam optimizer [15] with learning rate 10^{-5} and binary-cross-entropy [6] as loss function were chosen for both, described above, models training.

4. Training details

4.1. Stones segmentation

For the boundaries of the stones segmentation, the dataset № 2 was divided into three subsets: training set, which consists of 100 images; validation data – 20 images; test data – 14 images. For each considered image, 5 sub-images with size 1024×1024 pixels were randomly extracted (so-called cropping technique, thus we had 500 samples for training, 100 for validation and 70 for tests). The training was performed on 100 epochs with the batch size 1 sample. The obtained metrics are shown in Table 1 typical obtained inference results of stones segmentation are shown in Fig. 4.

Table 1. Results of training the U-net model for stones segmentation (Dice).

Metrics	train	valid	test
Dice	0.974	0.965	0.969

The results in Table 1 and Fig. 4 show a sufficiently high quality of the model inference without overfitting. The survey of staff in the mentioned above mining factory approves that obtained quality is high enough for the implementation of this model into theirs work.

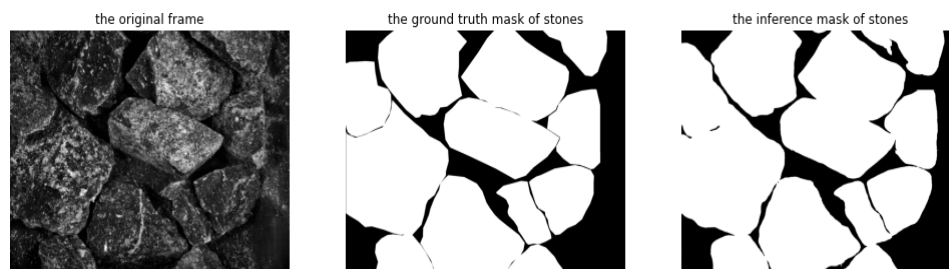


Figure 4. Typical results of stone segmentation inference using proposed neural network model

4.2. Asbestos veins segmentation

The model training for veins segmentation in the stones area was carried out in the two stages. At the first stage the model learning was carried out on the dataset № 1, which was divided on the 40 images for training part and 6 for test part. At the second stage the pretrained model was trained on the 15 images from dataset № 2 (with labeled veins), which was divided as 10 images in the training part, 3 in validation part and 2 in test part. Before training for each considered image in both datasets, 5 sub-images with size 1024×1024 pixels were randomly extracted (so-called cropping) and then decimated to size 512×512 pixels using bilinear interpolation. The obtained metrics are shown in Table 2. The typical inference results are shown in Fig. 5.

Table 2. Results of training the U-net model for stones segmentation (Dice).

Metrics	train	valid	test
Dice	0.747	0.711	0.605

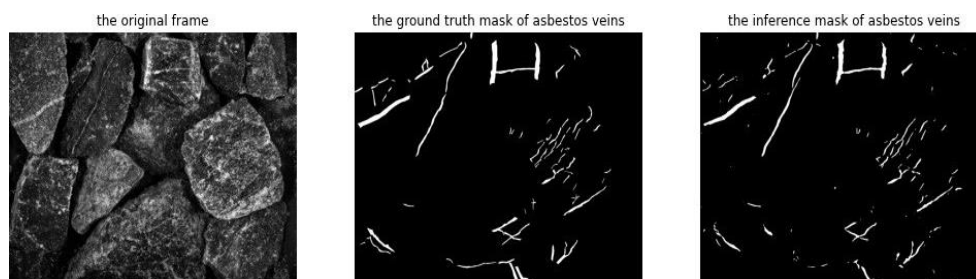


Figure 5. Results of asbestos veins segmentation using proposed neural network model

The results in Table 2 and Fig. 5 show a sufficient quality of the model inference without overfitting. However, the survey of staff in the mentioned above mining factory shows that it is not enough and this part of the work requires farther investigation.

5. Asbestos content estimation

The value of the specific asbestos content has proposed to estimate as to the average relation of all veins square to all stones square on the obtained image masks for both neural network models (see Figs. 5 and 4). This is based on the supposition that each asbestos vein runs right through the stone, and consequently, the surface area can represent the actual value of the asbestos content. Thus, the actual asbestos content can be estimated as follows:

$$Y = (k \cdot S_v / S_s + b) 100\% \quad (1)$$

where Y is the estimated value of the asbestos content; S_s , S_v are the average squares of the stones and veins correspondingly; k and b are the calibrations multiplicative and additive coefficients.

For checking the proposed method of asbestos content estimation, the comparison of estimated by (1) values given by the chemical laboratory results and given by developed system was carried out for the dataset № 2. For the automated annotation $k_1 = 0.398$, $b_1 = 1.131$; for the manual annotation $k_2 = 0.456$, $b_2 = 0.505$ these values are obtained by the least-square linear regression. The results are shown in Fig. 6.

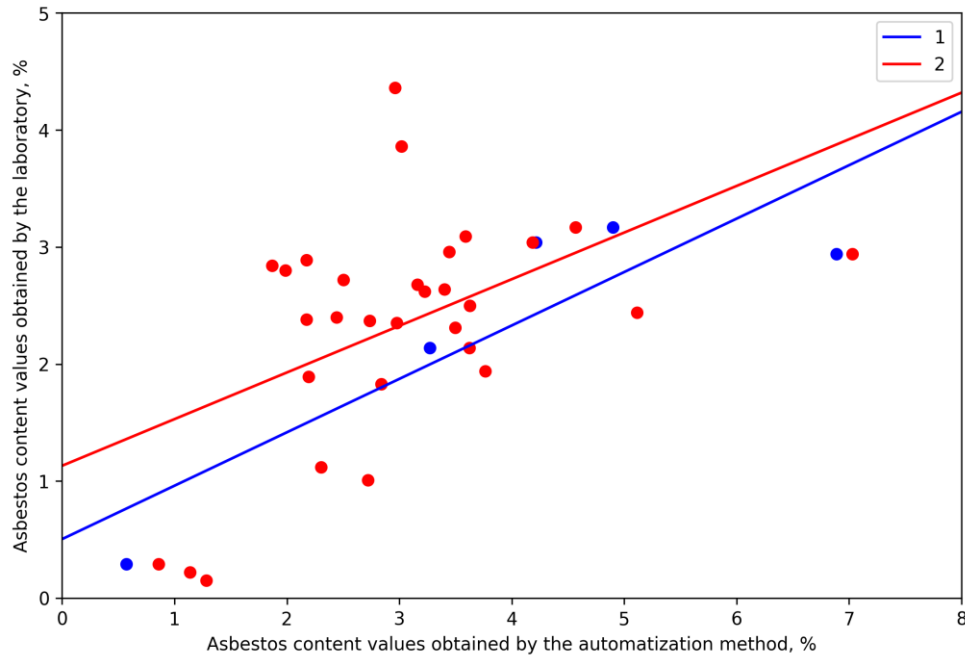


Figure 6. Relation of the asbestos content values estimated by equation (1) to the laboratory estimated values for the dataset № 2: line № 1 – the relation, for manual labelling of stones boundaries and asbestos veins (5 manually labeled samples); line № 2 – the relation, for obtained by proposed automatization method labelling of stones boundaries and asbestos veins (5 labeled samples applied for line 1 and 25 unlabeled samples)

Fig. 6 shows that relations № 1 and 2 are consistent in slope with each other with an average deviation of about 0.058 (k_1 and k_2). The bias difference for both lines (b_1 and b_2 difference about 0.628) can be explained due to the problem of wider veins boundaries highlighting in segmentation results.

As it was mentioned above the obtained accuracy is not sufficient in the industrial conditions. However, this result indicates that it is necessary to farther investing the asbestos veins segmentation

techniques. In our opinion, the quality of the veins segmentation model inference can be increase by datasets exceeding and applying more deep blocks in the encoder and decoder parts of the considered neural network, in particular by using such architectures as U-Net ++ [16].

6. Conclusion

During the described the first stage of the development of the computer vision system for the automatic asbestos content control in stones veins at an asbestos processing factory, the prototype of the system was created and investigated. The proposed system allows one to takes snapshots of asbestos stones on the conveyer belt in the near infra-red range without outer lighting influence, and its digital processing to estimate the asbestos content. The formed and manually labelled datasets were applied for training the proposed U-Net based semantic segmentation neural network. The network is applied both for stones boundaries and veins segmentation. By the obtaining results, it is proposed to estimate the asbestos content as the relation of the average square of veins to the square of stones. The resulted deviation between obtained values by the proposed method and laboratory-measured results: in slope (k_1 and k_2) is about 0.058; in bias (b_1 and b_2) is about 0.628. This value is high enough by our opinion. However, by the survey of mining processing factory stuff shows that this value is not enough, however, the quality of stones segmentation is sufficient high. In our opinion, the quality of the veins segmentation model inference can be increase by datasets exceeding and applying more deep blocks in the encoder and decoder parts of the considered neural network. Moreover, we are expecting that the slope deviation can be decreased by using the method of interval analysis. This method allows one to take into account both simultaneously the error of determination of asbestos concentration in laboratory condition and by the proposed method.

Acknowledgments

The work was supported by Act 211 Government of the Russian Federation, contract No 02.A03.21.0006.

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